Digital Twin-Assisted Optical Power Allocation for Flexible and Customizable SNR Optimization

Xuhao Pang[1], Shengnan Li[1], Qirui Fan[2], Min Zhang[1], Chao Lu[3], Alan Pak Tao Lau[2], and Danshi Wang[1,*]
[1]State Key Laboratory of Information Photonics and Optical Communications, Beijing University of Posts and Telecommunications (BUPT), Beijing, 100876, China
[2]Photonics Research Center, Department of Electrical Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China
[3]Photonics Research Center, Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China
*Email: *danshi_wang@bupt.edu.cn*

Abstract: A digital twin-enabled power allocation scheme is proposed to realize flexible SNR optimization using Autoencoder. Three customized SNR targets are achieved, which is useful for accurate margin planning in mixed-line-rate transmission systems.

1. Introduction

In multi-channel and multi-span optical transmission systems, the power evolution for each channel may excurse greatly and the quality of transmission (QoT) for each service is always non-uniform, which is mainly caused by the non-flat gain profile and noise figure (NF) of erbium doped fiber amplifier (EDFA), stimulated Raman scattering (SRS) and Kerr nonlinearity-induced interference (NLI) of fiber. To ensure power spectral uniformity, on the one hand, EDFAs are always equipped with gain flattening filters (GFFs) at the cost of insertion loss and higher power consumption; on the other hand, based on block [1] and end-to-end (E2E) [2] models, the power prediction and optimization using EDFAs without GFFs were realized by only controlling input power spectrum. However, these works only focused on the optical power optimization, but without considering signal-to-noise ratio (SNR) which is explicitly related to QoT. Accordingly, heuristic algorithms-enabled SNR optimizations were achieved by properly configuring EDFA gain/tilt [3] and allocating per-channel powers [4], whereas the iterative optimization-based heuristic algorithms were essentially time-consuming and only effective for the simple or single optimization tasks.

With the growth and deployment of 400Gb/s technique, multiple modulation formats at mixed line rates (100/200/400Gbps) are transmitted simultaneously in a fiber link at different wavelength channels [5]. To ensure the quality of each channel, different formats require different SNR levels at receiver. Previous works tried to flatten power distribution across channels, maximize worst SNR, and average SNR under the assumption of equal requirements or ideal EDFA, but ignoring the differentiation of mixed line rates. The flexible SNR optimization and customization can be used to match different SNR requirements according to the current link conditions so as to facilitating the accurate margin provisioning and efficient lightpath planning.

In this paper, a digital twin (DT)-assisted optical power allocation scheme is proposed to simultaneously realize the accurate SNR prediction and flexible SNR optimization using EDFAs with non-flat gain and NF. The mirror model is first built to perform the forward SNR prediction, and then transferred to the Autoencoder (AE)-based SNR optimizer. We only need to take the target SNR profiles as the input and output label of AE to train the encoder. In addition to flat SNR profile, other customized SNR targets (step and square-wave ones) can also be achieved within 2 seconds by only adjusting the launch powers of transmitters for short-reach transmission (< 5 spans), and cooperated with configuring attenuations of wavelength selective switch (WSS) for long-haul transmission (up to 10 spans). Compared with previous maximum SNR average and flatness optimization schemes, the proposed methods provide a more flexible and customizable solution of SNR optimization for the mixed-line-rate systems.

2. Scenarios and principle

Currently, DTs have become an enabling technology to connect the physical and network layers through building accurate mirror models to simulate and characterize the states and process of transmission system, and then based on the mirror models, the matching optimization strategies are made and fed back to physical layer [6]. In our scheme, each Optical Multiplex Section (OMS) consists of 5×100 km fiber, and both short-distance (single OMS) and long-distance (cascaded OMSs) cases are studied, as shown in Fig. 1(a), where the transmission link is abstracted from the network topology. To prove the scheme is feasible even in intractable cases, all EDFAs with non-flat gain profile and NF are without GFFs, leading to the distinct power excursions and large SNR ripples during transmission. First, in physical layer, for each transmitter, the initial SNR is set to 40 dB and launch power varies within -6~6 dBm. A total of 64 channels from 191.3625 THz to 196.0875 THz at 75 GHz grid cover the whole C-band. The parameters of fiber refer to the standard single-mode fiber (SSMF), where the nonlinearities of SRS, self-phase modulation (SPM), and cross-phase modulation (XPM) are taken fully into account. After 100 km transmission, all the channels are amplified

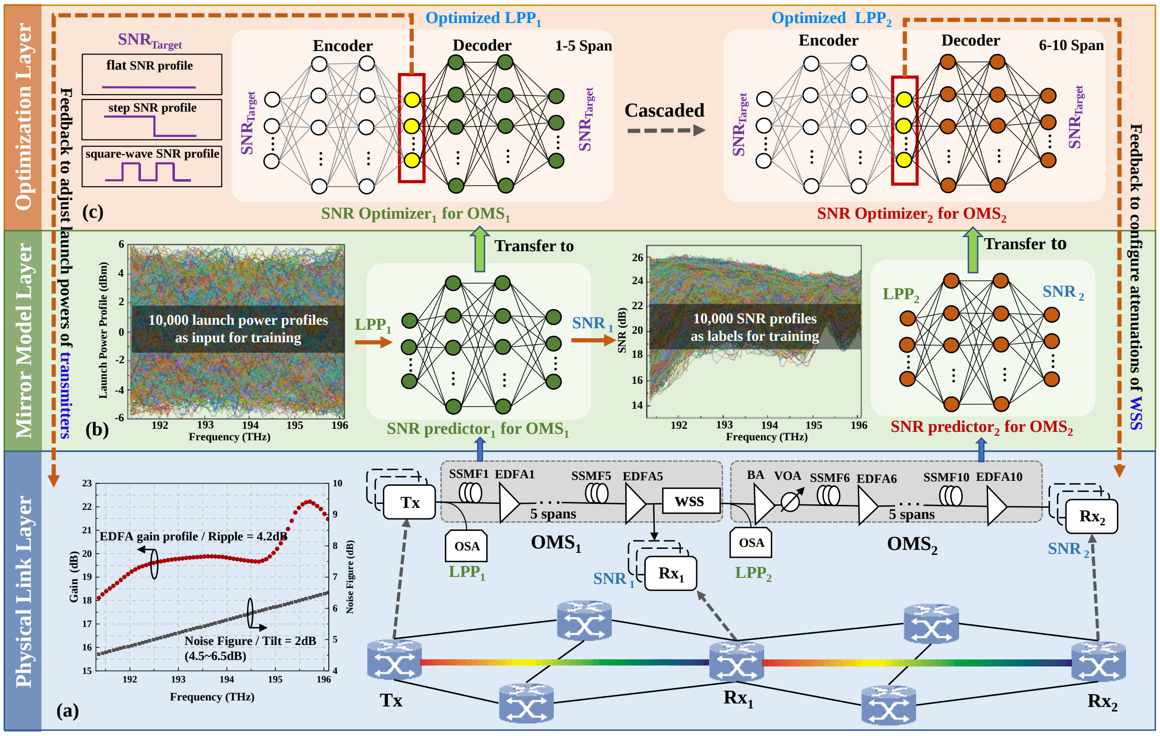

Fig.1 Framework of digital twin for SNR optimization: (a) Scenario and system setup in physical link layer; (b) NN-based SNR predictor in mirror model layer; (c) AE-based SNR optimizer in optimization layer to obtain the desired launch power profiles.

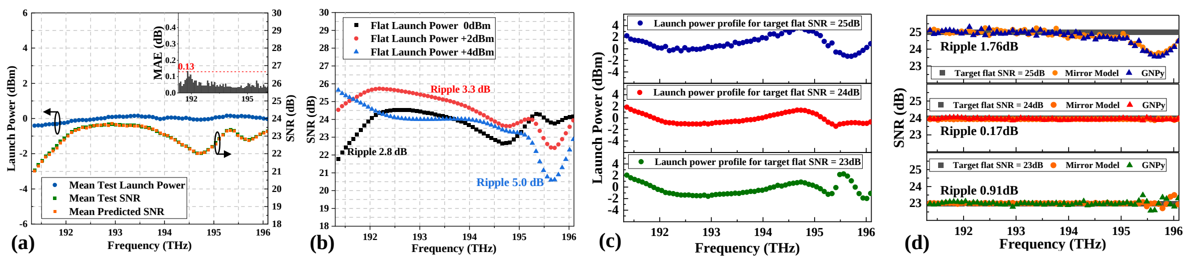

Fig.2. Test for OMS_1: (a) in 1,000 test data, mean launch power, mean SNRs, and mean predicted SNRs from NN; (b) received SNRs at different flat launch powers; flat SNR target: (c) three optimized launch power profiles from AE and (d) corresponding SNR profiles.

by an EDFA at the end of each span, whose gain profile and NF are referred from a commercial EDFA without GFF (seeing inset in Fig. 1(a)).

In DT layer, a mirror model is constructed for each OMS with a neural network (NN), which is composed of an input layer with 64 neurons corresponding to the launch power profile (LPP) for 64 channels, two hidden layers with 64×4 neurons, and an output layer with 64 neurons to predict the SNRs of 64 channels after transmission over one OMS. The SNR calculation is based on generalized Gaussian noise (GN) model, and system simulation and data generation are implemented by enhanced GNPy [7]. For the first OMS_1 (5 spans), the transmitted launch powers of each channel are adjusted from -6 to 6 dBm by parametrizing a smoothened Gaussian random walk [8]. To build the mirror model of OMS_1, total 10,000 pairs of random LPPs and SNRs are collected for training, and other 1,000 pairs for testing, as shown in Fig. 1(b). The mean predicted SNRs of NN and the real mean SNRs of GNPy from test data are displayed in Fig. 2(a). Two profiles are almost overlapped and the maximum mean absolute error (MAE) is < 0.13 dB, guaranteeing an accurate SNR prediction model. After OMS_1, an WSS followed by a booster amplifier (BA) is deployed to re-adjust the LPPs for the second cascaded OMS_2. Similarly, the mirror model of second OMS_2 is built by the other NN with 10,000 training data and 1,000 testing data, and the maximum MAE is < 0.07 dB.

Next, all the parameters of NN-based SNR predictor are fixed, and then the whole NN remains and is transferred to the AE-based optimizer directly to be the decoder. An AE composed of encoder and decoder presents a symmetrical structure, where the output data is equal to input data in an unsupervised manner [2]. In our scheme, the input and output of AE are the target SNR profiles that can be customized and designed flexibly to meet different SNR requirements depending on the link conditions, such as flat profile for uniform quality, step profile for mixed transmission under contiguous allocation, and square-wave profile for complex mixed transmission under random

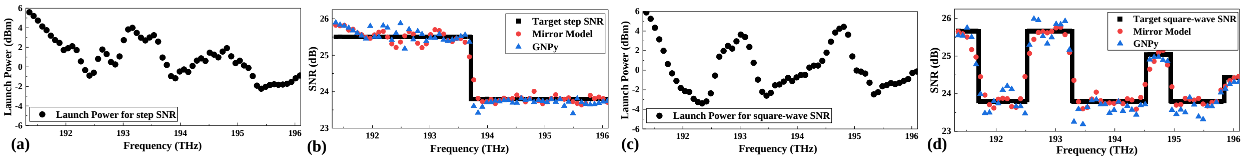

Fig.3. Step SNR target: (a) optimized launch power and (b) SNR profile. Square-wave SNR target: (c) optimized launch power and SNR profile.

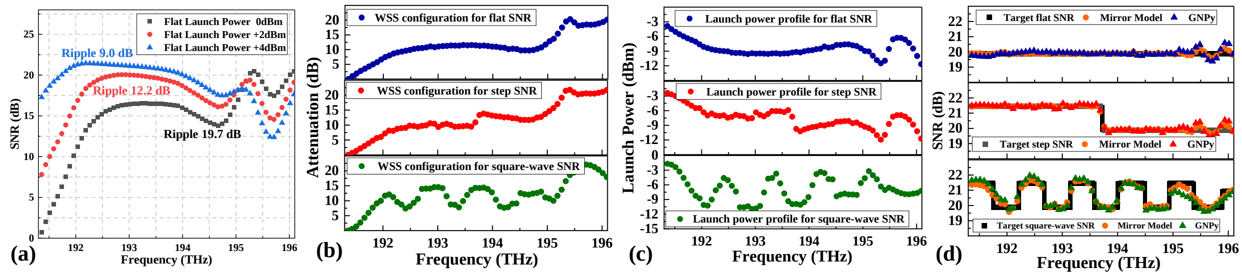

Fig. 4 Test for OMS_2: (a) received SNR of 10 spans at different flat launch power without optimization and WSS; three customized SNR targets (flat, step, square-wave): (b) WSS configuration on attenuation, (c) optimized launch power profiles, and (d) corresponding SNR profiles.

allocation. The target SNR profiles are used to adjust the parameters of encoder only, and the desired launch powers for target SNR profile can be obtained from the output layer of encoder. For OMS_1, the obtained LPP_1 is used to adjust the power of each transmitter; while for OMS_2, the obtained LPP_2 is used to configure the attenuation of WSS.

3. Results and conclusion

First, we study the case of single OMS_1. When the LPPs are flat at different launch powers (0, 2, 4 dBm), the SNR profiles present large ripples till to 5.0 dB, as shown in Fig. 2(b). Then AE-based SNR optimizer is trained with three flat SNR targets of 23, 24, 25 dB, and the total training time is less than 2 seconds which is much faster than heuristic algorithms (several minutes in general) [3, 4]. With the help of AE, three optimized LPPs are obtained (seen in Fig. 2(c)), and then sent to GNPy and NN-based mirror model respectively to generate the SNR profiles, as shown in Fig. 2(d). After optimization, the SNR ripples are obviously decreased, especially for second one, targeting the optimal flatness (ripple=0.17dB) with relatively large SNR average (24 dB). Next, other two customized SNR targets (step and square-wave ones) are further studied. For the step SNR target, 32 channels at low frequency domain are targeted to higher SNR (25.5 dB), serving for signals at high line rate and high-order modulation; while the other 32 channels at high frequency are targeted to lower SNR (23.8 dB) for other strongly robust signals. For the square-wave target, SNR profile is customized flexibly to adapt to the more complex mixed system where the signals carrying different levels of service are allocated randomly in C band. The optimized LPPs and generated SNR profiles are presented in Fig. 3. With the obtained LPPs, the customized SNR profiles, verified by GNPy and mirror model, are closely fitting to the target lines for both step and square-wave cases.

Next, the cascaded OMS_2 is studied for long-haul transmission optimization. Without any optimization, the received SNR profiles under flat LPPs after two OMSs (10 spans) experience extremely huge ripples, as shown in Fig. 4(a). In this situation, it is difficult to achieve flexible SNR optimization by only adjusting the LPPs of transmitters, so it is necessary to deploy an WSS at the end of OMS_1 to re-adjust LPP_2 for OMS_2 by setting attenuations of each channel. With the assistance of second AE-based SNR optimizer, the desired LPP_2 can be obtained, which can be used to calculate the attenuation setting of WSS by combining LPP_2 and power profile before WSS. Herein, three SNR targets (flat, step, and square-wave) are measured, and accordingly, the AE-generated LPP_2 and derived WSS configurations are shown in Fig. 4 (b)-(c). Finally, the customized SNR profiles are verified by GNPy and the mirror model as shown in Fig. 4 (d). It can be observed that the SNR profiles from GNPy are closely approximated to the target ones, and MAEs for three SNR targets are 0.12 dB, 0.12 dB, and 0.27 dB, proving the feasibility of this scheme for the long-haul transmission system.

In conclusion, this DT-assisted method can not only realize accurate SNR prediction, but also perform flexible SNR optimization. This provides a prospective solution for the accurate margin provisioning and efficient lightpath planning for the mixed-line rate transmission systems.

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